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Optimal design methodologies under the carbon emission trading program using MIP, GA, SA, and TS

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ABSTRACT

In this paper, an adaptation of MIP, GA, SA, and TS to network planning under the carbon emission trading program is described and computational results are given. As will be shown, the results are very encouraging. The cost function of this problem consists of the capital investment cost in discrete form, the cost of transmission losses, the power generation costs and carbon emission costs. The optimization model has the ability to minimize the total costs and provides the best solutions, which are both cost-effective and environmentally friendly. This method of solution is demonstrated on the real problem. Finally, the performance of the proposed procedure is compared with that of the most well-known as mixed-integer programming.

Contents

1. Introduction

The trading of carbon as one is considered as the carbon market these days. There is no limitation of GHG emission for the developing countries, thus they can sell their emission permits to the developed countries under the Kyoto Protocol. Therefore, the carbon emission trading schemes have become a procedure for the developed countries to avoid penalties from excessive pollutant emissions. Metcalf [1] proposed the corporate tax reform paying the bills with a carbon tax and measured the industry impacts of an environmental tax reform in which a carbon tax is used to finance full or partial corporate tax integration. Lutter and Shogren [2] showed that such ancillary benefits imply the unfettered price of carbon emission permits observed in tradable permit markets might significantly exceed the incremental social cost of controlling carbon emissions. This difference can help to justify market interventions such as an import tariff on permits traded internationally. Herber and Raga [3] proposed an international

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carbon tax to combat global warming and concluded that even though early adoption of the tax is unlikely, the economic merits of this tax instrument for the alleviation of global warming accompanied by changing political parameters may lead to its adoption in the long run. Spru [4] used the carbon trading in the policy mix and improved understanding of such interactions by examining the conditions under which a cap-and-trade scheme for carbon dioxide (CO_2) emissions may usefully coexist with carbon/energy taxes, support mechanisms for renewable electricity, and policies to promote energy efficiency. Monni et al. [5] estimated the uncertainties in different emission trading schemes based on uncertainties in corresponding inventories. Dumanski [26] discussed relationships between soil conservation, carbon sequestration, and the Kyoto Protocol. The Kyoto Protocol is the first attempt to use the flexibility of the global market place to stabilize and reduce GHG emissions, mitigate climate change, and promote sustainable development. Clementon [25] explored a first step on the difficult journey to a post-Kyoto Protocol agreement. Bohringer [6] provided a critical assessment of the Protocol's potential performance and discusses amendments to foster its effectiveness and efficiency. It concludes that, even without any effective emission reductions in the initial commitment period, the ratification of Kyoto is important for the further policy process of climate protection. The Kyoto Protocol has established a flexible, broad-based, international mechanism that provides a valuable starting point for shaping efficient climate policies in the future. Marbe and Harvey [7] proposed at exploring the role of policy instruments for promoting the use of low CO_2 emission fuels in high performance combined heat and power systems in the district heating sector. They presented the results of a case study for a Swedish district heating network where new large size natural gas combined cycle (NGCC) combined heat and power (CHP) is being built. Many regions, e.g. countries, have developed energy–economy models to assess their energy policies, in particular concerning the curbing of their CO_2 emissions. Furthermore, from a decision support perspective, the model can be used to integrate aspects of ecological sustainability (in relation to the climate change issue), economic welfare, efficient resource use and technological innovation. Nagurney et al. [8] developed a modeling and computational framework that allows for the determination of optimal carbon taxes applied to electric power plants in the context of electric power supply chain (generation/distribution/consumption) networks. The adoption of carbon/pollution taxes both internationally and regionally has been fuelled by global climate change and fuel security risks, with a significant portion of such policy interventions directed at the electric power industry. The general framework that they developed allows for three distinct types of carbon taxation environmental policies, beginning with a completely decentralized scheme in which taxes can be applied to each individual power generator/power plant in order to guarantee that each assigned emission bound is not exceeded, to two versions of a centralized scheme, one which assumes a fixed bound over the entire electric power supply chain in terms of total carbon emissions and the other which allows the bound to be a function of the tax. The behavior of the various decision-makers in the electric power supply chain network is described, along with the three taxation schemes, and the governing equilibrium conditions, which are formulated as finite-dimensional variation inequality problems. Twelve numerical examples are presented in which the optimal carbon taxes, as well as the equilibrium electric power flows and demands, are computed. The numerical results demonstrate, as the theory predicts, that the carbon taxes achieve the desired goal, in that the imposed bounds on the carbon emissions are not exceeded. Moreover, they illustrated the spectrum of scenarios that can be explored in terms of changes in the bounds on the carbon emissions; changes in emission factors; changes in the demand price functions, etc. Tabors and Monroe [9] discussed strategies for the US electric utility industry for reduction of both acid rain producing and global warming gases. The focus is on the northeast and east central regions of the USA. Strategies identified are fuel switching, mandated emission limits, and a carbon tax. The overall conclusions are that conservation will always benefit carbon emissions but may not reduce acid rain emissions by the offsetting forces of improved performance of new plant as opposed to reduced overall consumption of final product. Results of the study are highly utility and regional demand specific. They showed that significant reductions in both acid rain and global warming gas production can be achieved with relatively small increases in the overall cost of production of electricity and that the current dispatch logics available to utility control rooms are adequate to reschedule dispatch to meet these objectives. World concern has focused on rising levels of CO_2 in the atmosphere caused by burning fossil fuels. There is now evidence about supply problems of fossil fuels, especially oil for transportation. Dominic et al. [10] presented algebraic targeting techniques for energy sector planning with carbon (CO_2) emission and land availability constraints. In general, it is desirable to maximize the use of low- or zero-carbon energy sources to reduce CO_2 emission. However, such technologies are either more expensive (as with renewable energy) or more controversial (as in the case of nuclear energy or carbon capture and storage) than conventional fossil fuels. Thus, in many energy planning scenarios, there is some interest in identifying the minimum amount of low- or zero-carbon energy sources needed to meet the national or regional energy demand while maintaining the CO_2 emission limits. Via the targeting step of pinch analysis, that quantity can be identified. Besides, another related problem involves the energy planning of bio fuel systems in view of land availability constraints, which arises when agricultural resources need to be used for both food and energy production. Algebraic targeting approach of cascade analysis technique that was originally developed for resource conservation network is extended to determine targets or benchmarks for both of these problems. Since this paper involves the capital investment cost in discrete form, the cost of transmission losses, the power generation costs and the carbon emissions consideration, this fits with minimizing the total costs as the objective function in the mixed-integer programming (MIP). In some cases, MIP models require high memory and computational times due to special problems. There are a large number of researches relevant to the use of MIP models [11–18]. In mathematical programming, the drawback of these methods is that a very large number of decision variables are required and also, these methods require long computation times. In general, a characteristic of heuristic techniques is that strictly speaking an optimal solution is not sought; instead the goal is a "good" solution. Whilst this may be seen as an advantage from the practical point of view, it is a distinct disadvantage if there are good alternative techniques that target the optimal solution. With the development of artificial intelligence (AI) theory and techniques, some AI-based approaches to transmission network planning have been proposed. These include the use of expert systems (Galiana et al. [27]) and artificial neural network based methods . The main advantage of the expert system based method lies in its ability to simulate the experience of planning experts in a formal way. However, knowledge acquisition is always a very difficult task in applying this method. Moreover, maintenance of the large knowledge base is very difficult. Research into the application of the ANN to the planning of transmission networks is in the preliminary stages, and much work remains to be done. The potential advantage of the ANN is its inherent parallel processing nature. In recent years, there has been a lot of interest in the application of simulated annealing (SA) and tabu search (TS) to

solving some difficult or poorly characterized optimization problems of a multi-modal or combinatorial nature. SA is powerful in obtaining good solutions to large-scale optimization problems and has been applied to the planning of transmission networks. Tabu search has been applied successfully to many complicated combinatorial optimization problems in many areas including power systems [19]. The drawback of this method is that its effectiveness depends very much on the strategy for tabu list manipulation.

2. The model

The main purpose of emissions trading is to achieve effective environmental control. It is therefore important to ensure that implementation of the system does not entail too high an administrative or financial burden for regulating authorities or participating sources, and that it is designed in such a way as to ensure that specified environmental targets are achieved. In the case of pollutants that have local health or environmental impacts, this may require restrictions on total emissions by sources, on the direction of trades, or on the geographical area from which allowances/credits can be purchased, to ensure that trading ensures local environmental benefits. In all cases emissions trading require accurate monitoring of emissions and effective enforcement of compliance to ensure that the environmental target is achieved. The key elements of an emission trading schemes are as follows: (1) Targets: emissions trading schemes typically have a goal or emissions target. To date they have typically regulated stationary sources of pollution. (2) Permit allocation: the various methods of permit allocation are as follows: (a) Grandfathering: the grandfathering principle is commonly used in tradable permit schemes where allocations are based upon historic emission patterns, and appears to have a high degree of acceptability amongst participants, as it causes little disruption to existing patterns and minimizes the financial burden placed upon users. The grandfathering approach is used to allocate permits in the European Emissions Trading Scheme; (b) Auctioning: auctioning involves trading entities buying all their permits from the government. This has the advantage of creating funds that could be invested into the further development of the trading system or other things and reducing the financial burden. Auctioning can be used where either individuals or businesses are the trading entities; (c) Updating: updating involves an allocation based upon information on use which is updated over time. This method is popular with users but has disadvantages; in particular, users are able to increase their allocation by using more permits each year, thus increasing their allowance for the following period. This system is therefore inefficient as it may encourage greater use of the commodity rather than a reduction; (d) Free distribution: for businesses, permits could be allocated based on the size of the business or, for example, on the efficiency of current practices; (f) In practice, many schemes are likely to use a combination of the allocation methods described above. (3) Tradability: Permits can be tradable or non-tradable. Tradable permits can be passed between trading entities until they are finally consumed whereas non-tradable permits can only be used by the entity they were allocated to i.e. unused permits could not be sold to another player. (4) Geographical area: another important aspect of an emissions trading scheme is the geographical area to be covered within its remit. This could be on a regional, national or international level. (5) Temporal flexibility: within an emissions trading scheme, there can be an element of flexibility either in terms of meeting emission targets or distributing permits. In this paper, this is a novel model of the problem of minimum cost expansion of power transmission networks that is solved by MIP, GA, SA, and TS. The model explicitly takes into consideration the capital investment cost in its discrete form, the cost of transmission losses and the carbon emission costs. The model is also formulated to be applied with or without the cost of power generation. The DC load flow equations for the network are embedded in the constraints of this mathematical model to avoid sub-optimal solutions that can arise if the enforcement of such constraints is done in an indirect way. The solution of the model gives the best line additions, and also provides information regarding the optimal generation (MW) at each generation point. The theoretical basis of MIP is involved with minimizing and maximizing the linear objective function which is subject to a number of linear constraints. Transmission network planning is one of the factors that play an important role in supply management. Nowadays, it is well known that global warming has become the most serious threat because it could cause many disasters, such as extremely changed weather, heat wave, severe storm, etc. However, high quality transmission network planning can improve the global warming problems. Transmission network planning is said to be the most important sector emitting carbon to the atmosphere. Therefore, a design network and mode of transmission optimization model must be created considering carbon emissions trading. Its direct benefit is lowering the total costs and its indirect benefit involves environmentally friendly issues, especially, the global warming problems. Transmission optimization models are developed to enhance the decision-making procedure to choose: the number of generations, the amount of demands. They aim to meet the demands of finding the lowest costs and meeting targets of carbon emission trading. The optimization model is developed by using mixed-integer programming, GA, SA, and TS. Its structure can be divided into two parts: the objective function and constraints. For the review of literatures delivered so far, the understanding of how carbon emissions trading works has been achieved. Moreover, there are a number of major schemes based on carbon emissions trading, some of which are already in use but some are only proposed. All the schemes mentioned have the same target to reduce carbon emissions by means of a carbon trading mechanism. The proposed model is as follows:

The objective function: it refers to the purpose of the model which focuses on minimizing total costs consisting of capital cost of states of proposed lines, linearised cost coefficient representing transmission losses cost of states of proposed lines, linearised cost coefficient representing transmission losses cost of existing lines, cost of generating a unit of power at bus-bars, unit carbon emission cost of states of proposed lines, linearised cost coefficient representing transmission carbon emission cost of states of proposed lines, linearised cost coefficient representing transmission carbon emission cost of existing lines, carbon emission cost of generating a unit of power at bus-bars. The constraints comprise demands and capacity flows. The designed objective function and constraints (1–10) can be written as a formula and equation shown below:

Subject to:

1. The power balance constraint at nodes or the power flow conservation equation at each node upholding Kirchhoff's First Law.
2. It is advantageous to use exact DC load flow constraint equations based on the modified form of Kirchhoff's Second Law because the iterative process for line addition is not required. Hence, the computation time is decreased. The loop equations containing only existing lines, this constraint upholds Kirchhoff's Second Law for existing lines.
3. The loop equations for loops containing one proposed line. The DC load flow equations for the network are embedded in the constraints of the mathematical model to avoid sub-optimal solutions that can arise if the enforcement of such constraints is done in an indirect way.
4. The exclusivity constraint for each proposed lines; this constraint forces the program to select one state only for each

proposed line, or delete all its states. The exclusivity constraints result from the fact that the capacity of any line can take on only one value. That value, however, may be any of the discrete capacities in the cost-capacity curve. The exclusivity constraints prevent the capacity from assuming more than one value;
5. The overload constraint for each existing lines;
6. The overload constraint for the states of each proposed lines;
7. The generator capacity limit at each node;
8. The availability constraint at each node; this controls the number of lines connected to each node according to parameters;
9. The amount of power flows must be in positive numbers; power flow on existing lines from its start to its end, power flow on existing lines from its end to its start, power generation at bus-bars, power flow on states of proposed lines from its start to its end, power flow on states of proposed lines from its end to its start.
10. Zero–one integer variable assigned to states of proposed lines from its start to its end; zero–one integer variable assigned to states of proposed lines from its end to its start.

3. The real problem

This section is divided into four sections. The first section involves a comparison of calculated results of non-applied and applied carbon emission costs to mixed-integer programming. Secondly, the carbon emission costs are expanded to wider ranges (-20%, -10%, -5%, 5%, 10%, and 20%). The objective is to observe the feasible changes in the decision-making process when the carbon emission costs are increased or decreased. For the third section, the carbon emission costs are dramatically increased in order to simulate the commitment of penalty charges situation. The final section in this section proposes ways to reduce carbon emissions arising from the supply management.

3.1. Comparison of carbon emission costs

Fig. 1 shows flow chart of the design model. The results of the traditional procedure show total costs of 13558.98 and 0% of carbon emissions cost because carbon emissions are not considered in this case. This example is an actual system in the western part of China. The original network has 10 bus-bars and nine lines. The system consists of seven existing load buses and three existing generator buses. The system is to be expanded to 18 bus-bars with four new load buses added and four new generator buses. The net generation for each of the bus-bars and the specifications for the existing and proposed lines in the network are given in reference [20]. In this example, the cost of a circuit is defined as being directly proportional to the line length. The application of the developed method has been made in the light of the following factors: (1) only one line type is assumed; (2) the maximum number of states = 4; (3) the cost of a circuit is proportional to the line length; therefore, the line length can be used to replace the cost in comparison analysis.

The new legislation regulated carbon emissions will be included in transmission network planning. From the review of literatures, it can be seen that there are many carbon emission schemes proposed. This paper assumes the carbon emission costs from purchasing carbon permits from other companies having excess credits. Thus, the costs of carbon emissions become part of the total costs, which leads to an increase in total costs. The calculations in this case refer to the traditional procedure considering a new factor, carbon emission costs. This problem is resolved by using the Solver Parameter in Excel. The first step of calculations is assuming values for all the parameters to be calculated in the objective function and constraints. The minimized total costs and the carbon emission costs are 15584.09 and 2025.11, respectively. The carbon emission costs are shown to be 12.9% of the total costs. Due to the increase in the total costs, managers must find a new approach to making decisions considering carbon emission costs. The new approach is the intelligent optimization techniques.

3.2. Trends in decisions due to changes of carbon emission costs

In order to study the tendency of making decisions because of the changes of carbon emission costs, reducing and increasing the carbon emission costs by $\pm 5\%$, $\pm 10\%$, and $\pm 20\%$ are applied to the optimization model. The major reason is that unstable carbon prices in markets are predicted. Therefore, studying this expected situation by expanding the range of carbon emission costs leads to understanding the impacts on the decision-making process in the supply management. Table 1 shows the calculated results when changing the carbon emission costs.

From Table 1, it can be seen that the total costs are changed corresponding to only the increase and decrease in the carbon emission costs. However, in order to obtain further results, the next section will continue the study when the carbon emission costs increase dramatically.

3.3. Trends in decisions due to penalty charges

According to the literature review, the penalty charge of 40 EUR per tonne carbon was indicated in the first phase of the EU-ETS and 100 EUR per tonne carbon in the second phase. The current carbon prices mentioned in the previous section are 22–25 EUR per tonne carbon. The penalty charge of carbon emissions is higher than the market prices by 100% for phase I and 300% for phase II approximately. Thus, this study will increase the carbon emission costs by 100% and 300% in order to see whether or not the decisions will be impacted. Table 1 illustrates the results in cases of the penalty charge.

Table 1 shows the decisions after the carbon emission costs increase dramatically due to the penalty charge. There are some substantial differences in the individual line power flows although the fundamental structure is similar to only one difference in network topology, two differences in number of lines, and one difference in direction of flow. Now, it can be seen that the decision is changed when the carbon emission costs increase by 100% and/or more. Thus, it can be concluded that the decisions can be dramatically affected by changing only one factor which is the carbon emission costs in this case. This situation may happen in the future in case the demand for carbon permits is higher than the supply because there may be only a few carbon permits traded in the markets. In this case, many firms will incur the penalty charge due to the shortage of carbon permits.

Although the carbon market is rapidly growing, the carbon prices of 22–25 EUR per tonne of carbon cannot be said to be as high in the perspective of the carbon sellers, when compared to a high level of investment in new green technology. It is predicted that the carbon prices will be continuously rising. This can be an incentive driving companies and individuals to put an emphasis on reducing carbon emissions so that they can sell the carbon permits at high prices. In terms of environmental impacts on supply management, when carbon emissions trading is implemented, costs of industrial development will increase because of the investment in new types of green technology for reducing carbon emissions. Furthermore, implementing the carbon emissions trading schemes results in new business strategies because environmental issues are included in decision-making processes by considering the environmental impacts of proposed actions and alternatives to those actions.

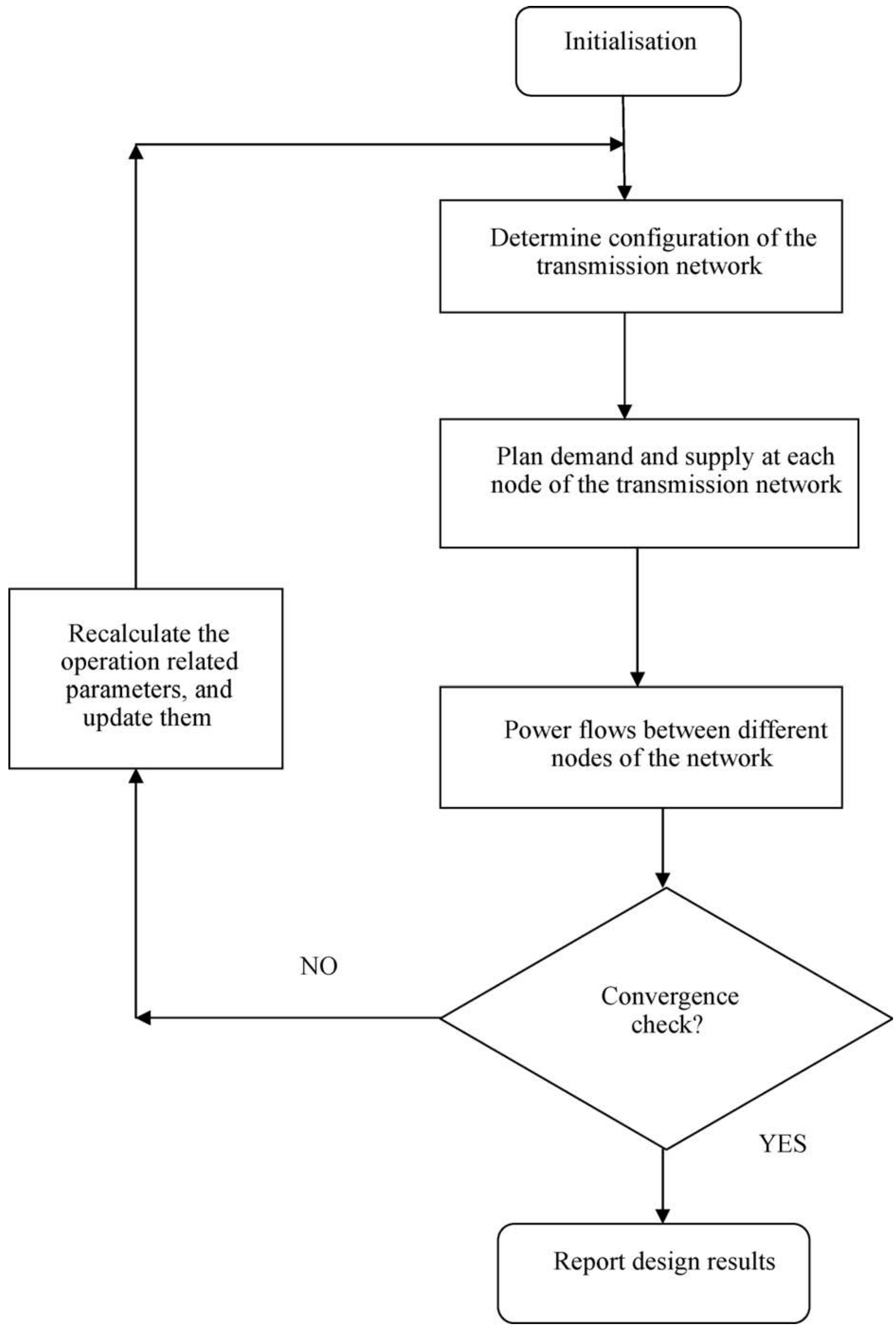

Fig. 1. Flow chart of the design model.

3.4. Methods for reducing carbon emissions

The energy costs, taxations, legislations, demands, etc. are all the factors that contribute to carbon emission strategies and decision-making processes. The approaches for reducing carbon emissions can be to necessitate a strategy to adapt companies themselves to environmental issues. Carbon emission reduction strategies can be beneficial because it encourages companies to analyse the solutions to green issues. This section will explain the possible procedures to reduce carbon emissions in the supply management.

3.4.1. Supply management and network planning

Supply management and transmission network design involves the decisions used to select suppliers, locations of facilities,

Table 1
Average iterations and calculated results after changing carbon emission costs using mixed-integer programming and genetic algorithm.

Ranges	−20%	−10%	−5%	MIP and GA	5%	10%	20%	100%	300%
Carbon emissions	1620.08	1822.59	1923.85	2025.11	2126.36	2227.62	2430.13	3643.858	5572.96
Total costs	15179.78	15381.57	15482.83	15584.09	15685.34	15786.60	15989.11	17252.33	19181.43
Ranges	−20%	−10%	−5%	GA	5%	10%	20%	100%	300%
Average iterations	6543	7652	5789	4328	6574	6541	7894	8904	9752

distribution centres and power flows through network. These decisions must be able to satisfy customers and to ensure competitiveness by minimizing the total costs consisting of fixed and variable costs of transmission, environment impacts and efficiency of resources. New developments are required to include in planning operations in the supply management so as to obtain environmental effective solutions Supply management and transmission network design result in positive changes of energy consumption. Environmental issues are added to the design as carbon emissions to obtain environmentally- and cost-effective decisions. In this case, new green developments are needed to be included in the supply management. In this paper, the design optimization model falls in this approach because it includes the carbon emission costs, which allows companies to obtain cost-effective and environmentally friendly solutions. Moreover, the collaborative network design can be advantageous. The collaborative transmission network design can lower carbon emissions per unit of products and the parties still have competitive advantages.

3.4.2. Global sourcing

Economic efficiency can be improved by global trading which allows companies to find their desired power flows from all over the world. The environmental impacts of buying power flows sourced from overseas are increasingly considered by consumer's ethical issues. However, this is not always true because carbon emissions must include manufacturing, transmission, etc. in the entire supply managements. Importing power flows from international sources may produce less carbon emissions than local sources. For instance, using international network to power flows from international sources can be more environmentally friendly than using domestic transmission network. Furthermore, the increase in fuel prices, limited transmission capacity, and carbon emissions trading will affect decisions of sourcing in the forthcoming future.

3.4.3. Lowering demands for network planning system

Avoiding transmission is one of the means for reducing carbon emissions. There are many factors that contribute to decreasing demands for transmission, most of which are related to rising fuel costs. However, carbon emissions arising from transmission are another major factor that companies should be aware of. Transmission avoidance can be considered as a procedure used to integrate transmission with production networks so as to avoid transmission networks. This means configurations of production and distribution can reduce the demand for transmission networks. Relocating facilities leads to carbon reduction.

4. Genetic algorithm

Optimization algorithms are divided into six categories as follows: (1) Trial-and-error optimization refers to the process of adjusting variables that affect the output without knowing much about the process that produces the output. In contrast, a mathematical formula describes the objective function in function optimization. Various mathematical manipulations of the function lead to the optimal solution. (2) If there is only one variable, the optimization is one-dimensional. A problem having more than one variable requires multidimensional optimization. Optimization becomes increasingly difficult as the number of dimensions increases. Many multidimensional optimization approaches generalize to a series of one-dimensional approaches. (3) Dynamic optimization means that the output is a function of time, while static means that the output is independent of time. (4) Optimization can also be distinguished by either discrete or continuous variables. Discrete variables have only a finite number of possible values, whereas continuous variables have an infinite number of possible values. Discrete variable optimization is also known as combinatorial optimization, because the optimum solution consists of a certain combination of variables from the finite pool of all possible variables. (5) Variables often have limits or constraints. Constrained optimization incorporates variable equalities and inequalities into the cost function. Unconstrained optimization allows the variables to take any value. A constrained variable often converts into an unconstrained variable through a transformation of variables. (6) Some algorithms try to minimize the cost by starting from an initial set of variable values. These minimum seekers easily get stuck in local minima but tend to be fast. They are the traditional optimization algorithms and are generally based on calculus methods. Moving from one variable set to another is based on some determinant sequence of steps. On the other hand, random methods use some probabilistic calculations to find variable sets. They tend to be slower but have greater success at finding the global minimum. Some outstanding algorithms have surfaced in recent times. Some of these methods include the genetic algorithm, simulated annealing, tabu search, particle swarm optimization, ant colony optimization, and evolutionary algorithms [21,22]. These methods generate new points in the search space by applying operators to current points and statistically moving toward more optimal places in the search space. They rely on an intelligent search of a large but finite solution space using statistical methods. The algorithms do not require taking cost function derivatives and can thus deal with discrete variables and no continuous cost functions.

Genetic algorithm is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the "fitness" (i.e. minimizes the cost function). Some of the advantages of a GA include that it

optimizes with continuous or discrete variables,
simultaneously searches from a wide sampling of the cost surface,
deals with a large number of variables,
is well suited for parallel computers,
optimizes variables with extremely complex cost surfaces (they can jump out of a local minimum),
provides a list of optimum variables, not just a single solution,
may encode the variables so that the optimization is done with the encoded variables, and
works with numerically generated data, experimental data, or analytical functions.

These advantages are intriguing and produce stunning results when traditional optimization approaches fail miserably.

The GA begins, like any other optimization algorithm, by defining the optimization variables, the cost function, and the cost. It ends like other optimization algorithms too, by testing for convergence. In between, however, this algorithm is quite different. A path through the components for the GA is shown as a flowchart in Fig. 2.

The GA begins by defining a chromosome or an array of variable values to be optimized. If the chromosome has N_{var} variables (an N_{var}-dimensional optimization problem) given by $pl_1, pl_2, \ldots, pl_{N_{var}}$, then the chromosome is written as an N_{var} element row vector:

$$\text{Chromosome} = [pl_1, pl_2, \ldots, pl_{N_{var}}]. \quad (1)$$

Each chromosome has a cost found by evaluating the cost function, Z, at $pl_1, pl_2, \ldots, pl_{N_{var}}$:

$$\text{Cost} = Z(\text{Chromosome}) = Z(pl_1, pl_2, \ldots, pl_{N_{var}}). \quad (2)$$

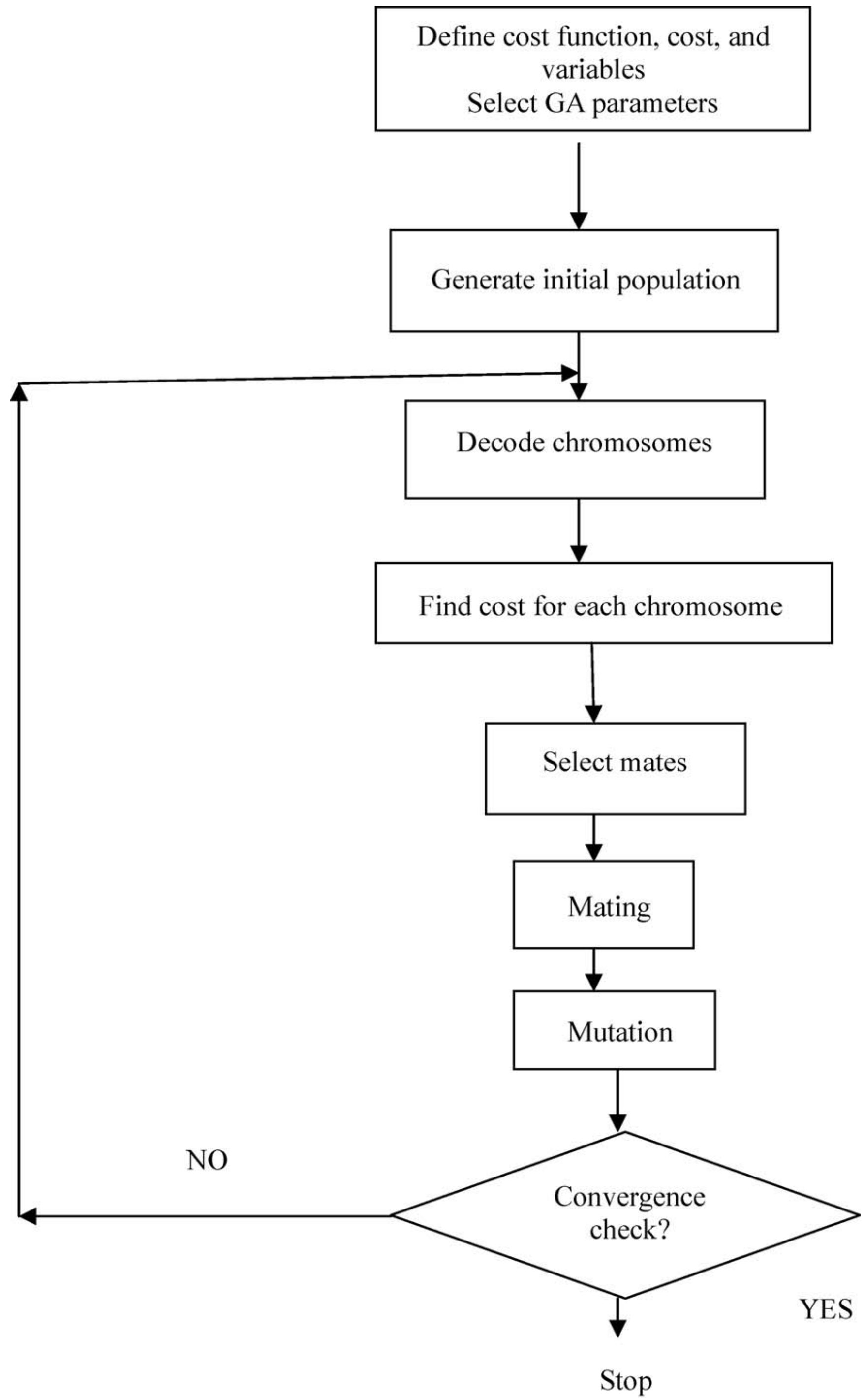

Fig. 2. Flowchart of genetic algorithm.

The chromosome structure used to represent a particular set of possible transmission line power capacities, for the mixed-integer transmission network planning using GA has 40 state variables. The GA works with the binary encodings, but the cost function often requires continuous variables. Whenever the cost function is evaluated, the chromosome must first be decoded. Each individual line capacity is encoded by sufficient bits to cover its allowable range of values. The bit strings for each variable are concatenated to form a chromosome. The initial population is generated randomly, that is, each bit in each chromosome is set randomly to either 1 or 0. Whenever a new chromosome is generated it is checked to see that in decoded form it produces valid values for the variables. When an invalid value is produced the chromosome is discarded and another one is generated. The GA starts with a group of chromosomes known as the population. The population has N_{pop} chromosomes. After the mutations take place, the costs associated with the offspring and mutated chromosomes are calculated. The process described is iterated. The number of generations that evolve depends on whether an acceptable solution is reached or a set number of iterations are exceeded. After a while all the chromosomes and associated fitness values would become the same if it were not for mutations. At this point the algorithm

should be stopped. The spreadsheet model is developed for solving this problem. In the next step for solving the system planning using a GA, equations are used to penalise solutions in the cost function. The final step in the implementation of the system planning using a GA is the fitness function. The fitness value of a chromosome is a measure of how well it meets the desired objective. In this case the objective is the minimization of the network's cost function. Choosing and formulating an appropriate objective function is crucial to the efficient solution of any given genetic algorithm problem. When designing an objective function for an optimization problem with constraints, penalty functions can be introduced and applied to individuals that violate the imposed constraints. The fitness function in equation (1) with penalty functions is used to calculate the fitness value of each individual. In this paper, for each combination of the parameters - crossover rate 0.17, 0.86, 0.91, mutation rate 0.0017, 0.0063, 0.360, population size 70, 115, 190 – the GA is run for nine different random initial populations – these nine populations being different for each combination. Thus, in total, the GA is run two hundred and forty three times. In order to study the tendency of making decisions because of the changes of carbon emission costs, reducing and increasing the carbon emission costs by ±5%, ±10%, ±20%, 100% and 300% are applied to the genetic algorithm. Table 1 shows the effects of unstable carbon emission costs on the total costs and the results obtained with the genetic algorithm. These results are the same as that obtained with mixed-integer programming. Table 1 also shows average iterations of effects of changing carbon emission costs by genetic algorithm.

5. Simulated annealing

The simulated annealing is a general optimization technique for solving combinatorial optimization problems. The algorithm is based on randomization techniques. However, it also incorporates a number of aspects related to iterative improvement algorithms. Since these aspects play a major role in the understanding of the simulated annealing algorithm. The application of an iterative improvement algorithm presupposes the definition of configurations, a cost function and a generation mechanism. Iterative improvement is therefore also known as neighborhood search or local search. The algorithm can now be formulated as follows. Starting off at a given configuration, a sequence of iterations is generated, each iteration consisting of a possible transition from the current configuration to a configuration selected from the neighborhood of the current configuration. If this neighboring configuration has a lower cost, the current configuration is replaced by this neighbor; otherwise another neighbor is selected and compared for its cost value. The algorithm terminates when a configuration is obtained whose cost is no worse than any of its neighbors. The disadvantages of iterative improvement algorithms can be formulated as follows: (1) By definition, iterative improvement algorithms terminate in a local minimum and there is generally no information as to the amount by which this local minimum deviates from a global minimum; (2) The obtained local minimum depends on the initial configuration, for the choice of which generally no guideline are available; (3) In general, it is not possible to give an upper bound for the computation time. To avoid some of the aforementioned disadvantages, simulated annealing is introduced by Kirkpatrick et al. [22]. Solutions, obtained by simulated annealing, do not depend on the initial configuration and have a cost usually close to the minimum cost. Furthermore, it is possible to give a polynomial upper bound for the computation time for some implementations of the algorithm. Thus, simulated annealing can be viewed as an algorithm that does not exhibit the disadvantages of iterative improvement and remains as generally applicable as iterative improvement. Annealing denotes a physical process in which a solid in a heat bath is heated up by increasing the temperature of the heat bath to a maximum value at which all particles of the solid randomly arrange themselves in the liquid phase, followed by cooling through slowly lowering the temperature of the heat bath. In this way, all particles arrange themselves in the low energy ground state of a corresponding lattice, provided the maximum temperature is sufficiently high and the cooling is carried out sufficiently slowly. In simulated annealing, the following elements must be provided: (1) a representation of possible solutions, (2) a generator of random changes in solutions, (3) a means of evaluating the problem functions and (4) an annealing schedule—an initial temperature and rules for lowering it as the search progresses. It is a robust and general technique. Its main advantages over other local search methods are its flexibility and its ability to approach global optimality. The algorithm is quite versatile since it does not rely on any restrictive properties of the model. SA methods are easily tuned. For any reasonably difficult nonlinear or stochastic system, a given optimization algorithm can be tuned to enhance its performance and since it takes time and effort to become familiar with a given code, the ability to tune a given algorithm for use in more than one problem should be considered an important feature of an algorithm. There is a clear tradeoff between the quality of the solutions and the time required to compute them. The precision of the numbers used in implementation is of SA can have a significant effect upon the quality of the outcome. It should be expected that GA may be better suited for some problems than SA. Similarly to simulated annealing, evolutionary algorithms are stochastic search methods, and they aim to find an acceptable solution where it is impractical to find the best one with other techniques. The simulated annealing algorithm was employed to solve the problems of combinatorial optimization of network systems. The same 40-bit binary string representation scheme applied in the case of the genetic algorithm was implemented for simulate annealing because of its flexibility and ease of computation. The cost function for this problem is objective function given in reference [13]. In this case the objective is the minimization of the network's cost function, so the fitness value is the reciprocal of this cost. The annealing process started at a high temperature, $T = 1150$ units, so most of the moves were accepted. The algorithm was implemented in Turbo C++. The initial stopping criterion was set at a total unit cost of optimal solution found by the genetic algorithm. Three cooling rates were used (0.33, 0.59, and 0.88). With 0.33, the temperature reduced rapidly. With the cooling rate set to 0.59 the cooling rate was medium. For 0.88, the rate of cooling was very slow. The final total costs function is showed in Table 2. The carbon emission costs by ±5%, ±10%, ±20%, 100% and 300% are applied to the simulated annealing. Table 3 shows the effects of unstable carbon emission costs on the total costs and the results obtained with the

Table 2
Calculated results after changing carbon emission costs using simulated annealing.

Ranges	−20%	−10%	−5%	SA	5%	10%	20%	100%	300%
Average iterations for the cooling rate = 0.33	14321	12675	13567	11231	12678	13987	15432	16123	16987
Average iterations for the cooling rate = 0.59	7689	6342	8764	6908	7621	8765	8123	11890	12098
Average iterations for the cooling rate = 0.88	11932	15987	12543	10987	13245	13435	12876	17654	18765

Table 3
The average of iterations for GA and SA.

Methods	GA	SA, cooling rate = 0.33	SA, cooling rate = 0.59	SA, cooling rate = 0.88
Average iterations for carbon emissions cost [2025.11]	4328	11231	6908	10987
Average iterations for carbon emission costs [−20%:+20%, 100%, 300%]	7108.5	14111.2	8688.8	14158.2

Table 4
Calculated results after changing carbon emission costs using tabu search.

Ranges	−20%	−10%	−5%	TS	5%	10%	20%	100%	300%
Average iterations	7678	8678	9321	8456	8889	7986	7623	9907	10987

simulated annealing. These results are the same as that obtained with mixed-integer programming and genetic algorithm. Table 2 also shows average iterations of effects of changing carbon emission costs with different the cooling rates by simulated annealing.

Table 3 shows the average of iterations of genetic algorithm and simulated annealing. The average of iteration for GA is 4328 while carbon emission cost is 2025.11. But the best result of SA shows that the average of iteration is 6908 when the cooling rate is 0.59. It can be seen that an improvement of 37.34% is achieved by the genetic algorithm. The results also show that the average of iterations for GA and SA are 7108.5 and 12319.4 respectively, when carbon emission is in range [−20%:+20%, 100%, 300%] and the cooling rate for SA is 0.33, 0.59, and 0.88. Therefore an improvement of 42.29% is achieved by the genetic algorithm.

6. Tabu search

Tabu search as proposed by [23,24] has proven to be a very effective meta-heuristic for hard problems. The problem to be solved can be expressed in the form of reference [13]. Tabu search can be described as an improvement on the standard hill climbing search defined relative to a neighbourhood structure and an evaluation function. A function must be specified for move evaluation. The function usually resembles reference [13], but may differ in order to take advantage of special knowledge of the problem. In cases where infeasible solutions are allowed during the search, a function for move evaluation is constructed to encourage discovery of feasible solutions. A hill climbing algorithm begins with an initial solution and selects solutions at iteration. Such an algorithm will eventually get stuck at a local minimum. To alleviate this problem, tabu search algorithms make use of a tabu list to force the search away from solutions selected for recent iterations. Moves are rejected if they satisfy conditions given by the tabu list which can be thought of as a First-In-First-Out (FIFO) list based on certain attributes of the most recent moves. This paper refers to such a tabu list as an attribute-based list. In this case, vectors that are the result of moves having the attributes found on the tabu list are removed from consideration unless they meet an aspiration criterion. The aspiration criterion is used to avoid removing very good moves from consideration.

The tabu list enables a tabu search algorithm to escape local minima which result in the termination of a simple hill climbing algorithm. Attribute-based tabu lists typically serve two purposes:

Avoidance of cycling, in order to escape a local minimum, the search must be prevented from "falling back" to a recently visited solution. Unless randomness is used in move selection, it is easy to see that if a solution can be revised, the algorithm may cycle infinitely.

Trajectory, by making certain move attributes tabu, an attribute list often prevents the "reversal" of moves. This results in exclusion of many solutions that have not yet been visited. In many instances this is desirable because it forces the search algorithm to explore new regions the aspiration criterion precludes the avoidance of any excellent solutions.

Use of the tabu list for both purposes forces the algorithm designer to make tradeoffs. One would expect that cycling is reduced by increasing the list length and the generality of the move attributes used. On the other hand, one would expect that the characteristics that result in the best trajectory are problem specific and non-monotonic. The basic tabu search framework has since been broadened to form a meta-heuristic that promotes search intensification and diversification through the creative use of short term and long term memory processes. Empirical results indicate that tabu search methods yield high quality solutions to a variety of difficult problems [23,24]. The carbon emission costs by ±5%, ±10%, ±20%, 100% and 300% are applied to the tabu search algorithm. Table 4 shows the effects of unstable carbon emission costs on the total costs and the results obtained with the tabu search. These results are the same as that obtained with mixed-integer programming, genetic algorithm and SA. Table 4 also shows average iterations of effects of changing carbon emission costs by tabu search.

It shows that tabu list size rate has an insignificant effect on convergence. However, when the poorer tabu sizes are used too low or too high then average number of iterations does have a significant effect. It was found that genetic algorithm performed best compared to other two artificial intelligence techniques and gave 19.5% and 18.1% improvements of tabu search and simulated annealing respectively (see Table 5).

It could be argued that the results demonstrate the validity of the simulated annealing method and tabu search since they achieve a 'very good average' iterations. However, the simulated annealing and tabu search approach does not provide us with a generic engineering tool. The results support the argument that genetic algorithms reduce the need for simulated annealing method and tabu search since ultimately it targets an optimal solution whilst being easily adapted to different applications and, consequently, a generic engineering tool. The results presented here support the extension of this argument into the field of topological configuration of power system in particular. The results of the experiment have confirmed that the cooling rate determines the quality of the iterations. Overall simulated annealing and tabu search needed longer computation times compared to the genetic algorithm. The drawback of simulated annealing is that its effectiveness depends very much on the strategy for cooling rates

Table 5
Average of iterations for GA, SA, and TS.

Genetic algorithm	7108.5
Simulated annealing: cooling rate [0.59]	8688.8
Tabu search	8836.1

[0.33:0.88]. Genetic algorithms are suitable for traversing large search spaces since they can do this relatively rapidly and because the mutation operator diverts the method away from local optima, which will tend to become more common as the search space increases in size. Furthermore, genetic algorithms can work on very large and complex spaces. These properties give genetic algorithm the ability to solve many complex real-world problems.

7. Conclusion

The alternative policy approaches to a tradable permit scheme are as follows: (1) Carbon tax on fuel, fuel tax increases are an alternative approach to tradable permits. Using price flexibilities of fuel demand, it would be possible to design a system of fuel price increases that could achieve significant reductions in CO_2 emissions; (2) Mandatory enforcement of clean technology/fuel, fuel producers could be forced to achieve preset environmental standards with the aim of reducing greenhouse gas emissions from the transmission network planning. Several approaches to emissions trading were investigated, there were certain strengths and weaknesses identified amongst the various options. Inevitably, in an emissions trading scheme, there are tradeoffs between the key issues surrounding acceptability, equity, efficiency and costs. These issues become more or less apparent depending on the system design, in terms of scope, permit allocation and monitoring processes and efficiency. The various carbon emission control methods are: tax models; trading schemes; system of fuels; political acceptability control costs; global climate change policy; improving generators maintenance standards; global and local emissions; lowering demands for transmission and global sourcing.

In this paper, mixed-integer programming and three artificial intelligence techniques, genetic algorithm, simulated annealing, and tabu search have been proposed to search for solutions to power network planning. The performance of each of the techniques is studied and the results compared with these from conventional methods. Finally, the algorithm was applied to a real data set, and the genetic algorithm proved to be a better scheduling method than the simulated annealing and TS and iterations of simulated annealing and TS are more than the genetic algorithm. The value of the cooling rate is significant in the broad range [0.33:0.88]. GA, SA and TS are well-known flexible heuristics for handling difficult combinatorial optimization problems. They have been adapted successfully to a large collection of applications. Several implementations of GA, SA, and TS have been proposed and compared to a mixed-integer programming. As computational results indicated, the GA, SA, and TS algorithms were able to obtain good quality solution in a reasonable amount of time even for large size problems. It is clear that all the GA implementations provide better solutions in significantly less computational time than the simulated annealing and tabu search algorithm. With its simplicity and generality, GA seems to be an efficient technique for solving large and complex network planning problems. Since the proposed approach did not exploit the particular structure of the problem, it should be relatively easy to adapt it for solving similar problems complicated by additional constrains. The results obtained are also very encouraging with regards to the perspectives of application of GA, SA, and tabu search to mixed-integer programming problems, in particular to those with an underlying network structure.

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